**The Thesis Committee for Robert Wayne Ressler**
**Certifies that this is the approved version of the following thesis:**

# The Role of Educational Nonprofits in the Early School Achievement of Children from Diverse Backgrounds

**APPROVED BY**
**SUPERVISING COMMITTEE:**

**Supervisor:**

______________________________
Robert Crosnoe

______________________________
Pamela Paxton

# The Role of Educational Nonprofits in the Early School Achievement of Children from Diverse Backgrounds

by

**Robert Wayne Ressler, BA**

**Thesis**

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

**Master of Arts**

**The University of Texas at Austin**

**May 2015**

# Acknowledgements

This thesis would not have been possible without the help of Robert Crosnoe, Pamela Paxton, Chandra Muller, Carmen Gutierrez, the staff and resources of the Population Research Center and my friends and family.

# Abstract

## The Role of Educational Nonprofits in the Early School Achievement of Children from Diverse Backgrounds

Robert Wayne Ressler, MA

The University of Texas at Austin, 2015

Supervisor: Robert Crosnoe

Nonprofit organizations represent a potentially powerful source of intervention for struggling public educational services, yet little is understood concerning the relationship between nonprofit providers and the educational outcomes of children. This study uses national data sets from the National Center for Educational Statistics and the National Center for Charitable Statistics to examine the associations between three theoretically derived nonprofit measures (competitor, intervener, and youth developer nonprofits) and student academic outcomes in math and reading over the crucial school-entry transition period. Results indicate that the number of nonprofits in a community display some positive associations with math and reading score gains, but that these associations must be carefully interpreted in regards to the heterogeneity of nonprofit service and the socio-economic context of the child.

# Table of Contents

## List of Tables

## List of Figures

The challenges that American schools face today are wide ranging, from underperformance in science and math (National Science Board 2014) to the disproportionate attainment of students from diverse backgrounds (Duncan and Murnane 2014). Innovative solutions are desperately needed to meet these challenges. One area that shows particular promise concerns intervention during the years surrounding a child's transition into school, which are the foundation of the entire educational career and a driving force in educational disparities. As such, investments in students during this period return higher rewards than at other points in the educational timeline (Heckman, 2006; Alexander, Entwisle, and Olson 2007). The best way to provide these investments, however, is often less understood.

One understudied source of investments in this growing field of research concerns the potential for outside organizations, such as nonprofits, to support the educational mission of schools. This lack of attention to the nonprofit sector is notable for theoretical reasons, given the emphasis of general systems theory on the interconnected nature of institutional and ecological actors in individual outcomes (Bertalanffy 1969). It is also notable for practical reasons, given the increased attention to school-community partnerships as a means of addressing educational problems in major educational policies such as No Child Left Behind (NCLB; U.S. Department of Education 2002) and the growing awareness that the effectiveness of government and charitable spending needs to be better assessed (Garrett and Rhine 2010).

In this spirit, this project integrates underutilized governmental data with widely used educational data to examine the potential for the presence of youth-focused educational nonprofits in a community to promote student success in that community's schools. Specifically, it adds zip code-level data on the quantity and type of educational nonprofits to the Early Childhood Longitudinal Study-Birth Cohort (ECLS-B) and Kindergarten Cohort (ECLS-K), applies multilevel modeling to these combined data sets, and examines whether the nonprofit makeup of a community predicts growth in achievement and reduces socioeconomic disparities in such growth during and after the start of elementary school. Doing so answers the challenge from Pianta and Walsh (1996, p. 76) for researchers to develop "a coherent set of principles…to understand the activity of [the systems of education], how they behave, how they change, and ultimately, how to predict their functioning with respect to the outcomes of schooling."

The larger context of this study is the flow of funding (measuring billions of dollars) from government, businesses, and individuals to nonprofits aiming to reduce social problems (Roeger, Blackwood, and Pettijohn 2012; Epstein and Buhovac 2009). When individuals and business utilize tax deductible donations, this directly removes money from public coffers and often does not redistribute it efficiently (Reich 2005). In general, this revenue flow diverts funding from improving public services, often with the implicit or explicit argument that due to market characteristics these organizations are more effective than those public services (Anheier 2005; Clotfelter 1992; Odendahl 1991). Importantly, this argument has been subjected to little systematic investigation concerning the effectiveness of nonprofits and other similar organizations, especially during the critical school transition period. This study, therefore, takes some of the first steps necessary to formulate a better understanding of these often forgotten organizational factors that may influence children's success in school at a time when it has such far-reaching consequences for them and society at large.

*The Educational Problem*

Recently, the U.S. educational system has been criticized as falling behind many other developed countries in producing highly skilled students for the global workforce (National Science Board 2014). It also appears to be complicit in the reproduction of inequality, as evidenced by the enduring racial/ethnic and socioeconomic disparities in numerous educational outcomes that public schooling is supposed to reduce (Darensbourg and Blake 2014, Bates and Glick 2013, Education at a Glace 2007, Ackerman, Brown, and Izard 2004, Jencks et al. 1972). Importantly, these disparities exist before children even enter school. Children from low-income families, for example, score significantly lower than children from middle- and upper-class homes on math and reading tests at the beginning of kindergarten (Lee and Burkam 2002). These initial disparities then increase over time as children move through the educational system and are subjected to stratifying forces like ability grouping, teacher expectations, and between-school differences in quality (Alexander et al. 2007). Thus, the window surrounding the transition into school—the year before the start of kindergarten and the kindergarten year itself—makes up one of the most important periods in students' long-term educational trajectories and represents a critical point for interventions aiming to improve the academic prospects of children and reduce disparities among child groups (Pianta, Cox, and Snow 2007, Varnhagen, Morrison, and Everall 1994). If the public educational system is going to address this reproduction of inequality and boost its overall effectiveness, the years surrounding the transition into formal schooling are of the upmost importance.

These pressing issues confronting the public educational system necessitate innovative solutions that will require input from numerous actors, both inside and outside of schools. This need for school-community partnerships was recognized twenty years ago when the 1994 Congress passed the Goals 2000 report (Epstein 1995) and then reiterated in the NCLB legislation (NCLB 2002) as well as in numerous state-level educational practices (National Education Association 2011). This policy conceptualization of communities as partners with the institutions serving them dovetails with sociological conceptualizations of communities as elastic political constructs that involve the active participation of individuals in order to maintain real existence (Collins 2010). I argue that nonprofit organizations—defined by the federal government and the National Center for Charitable Statistics as tax exempt 501c3 organizations (NCCS 2002)—embody both conceptualizations of community. First, they can be partners interested in investing in and supporting an institutional structure that serves the well-being of children in a community. Second, they can be active participants in the social defining of the communities that they both draw on and serve.

Leaving aside the unfortunate dearth of theoretical analysis concerning the specific role of such third-party actors within the educational system, nonprofits represent a potentially powerful vehicle for policy intervention in this system, especially in an era of shrinking government programs supporting children and their educational endeavors (Clotfelter 1992). This logic is reflected in economic perspectives that position nonprofits, along with the private and public sectors, as a channel of resource mobilization through which social problems can be addressed (Weisbrod 1972). Because the nonprofit sector is supported by both government and business and has been historically portrayed as a counterweight to failing public services (Clotfelter 1992), it is a meeting point in this synergistic resource mobilization within communities. Additionally, scholars have linked nonprofits to community socioeconomic characteristics (Katz 2014; Allard 2009) political culture (McDougle and Lam 2014, Bielefeld 2000) and altruism (Rose-Ackerman 1996) with an increased focus on the importance of nonprofit service provision in today's modern economy (Anheier 2014; Salamon, Hems, and Chinnock 2000). In the educational context, nonprofits that focus on improving the outcomes of school-aged children may represent a critical component for the success of the public education system, or, more troublingly, their presence may only exacerbate existing inequalities (Odendahl 1991). This research represents a first pass at attempting to evaluate this public-nonprofit relationship on the national level.

*Aims of the Study*

Utilizing a conceptual model in which nonprofits represent a significant proportion of "community partners" that interact with public schools and families to promote child-wellbeing (see Figure 1), this study aims to examine the diverse ways that nonprofits in a community may support the educational mission of schools in that community. The general goal is to examine the association between the community presence of educational nonprofits and the test scores of the children as they transition into elementary school. More specific goals then concern potential policy relevant sources of variability in this basic association.

[Figure 1 About Here]

To begin with the general goal, the nonprofit makeup of a community might be associated with the academic performance of students in a community's schools through two separate but not mutually exclusive mechanisms: competition and supplementary support. Beginning with competition, educational organizations and activities that offer alternatives to traditional public schools may trigger general educational improvements across the board by stimulating innovation through competition (Zimmer and Buddin 2009). In other words, if nonprofits provide alternative educational opportunities to schools, they can spur improvements in both private and public options that eventually lead to better performance across the board. For example, this logic has been applied to investigations of the impact of charter schools on traditional public schools and while there is some contention regarding the true nature of this impact some studies have revealed positive effects of charter schools on public school outcomes (Sass 2006; Bettinger 2005). Turning to supplementary support, many nonprofits' missions are to promote the success of community members, thereby directly and indirectly adding onto (or complementing) school services for children. For example, Leventhal, Dupéré, and Shuey (forthcoming: 152) argue that, "the quantity, quality, diversity, and affordability of programs and resources at the neighborhood level are an aspect of neighborhoods that is likely to be important for child development, as well as a potential pathway through which neighborhood structural characteristics may influence child development." If there are more nonprofits in an area specifically organized to improve child educational outcomes, then some impact of these neighborhood resources on children's actual outcomes would be expected.

This study uses the National Taxonomy of Exempt Entities (NTEE) to tease apart these potential explanations for any observed association between community-based nonprofits and the outcomes of public school students by grouping nonprofit organizations based on whether they represent separate competitive alternatives to public schools or provide services to schools. Although their services might differ, the roles of both competing and supplementary support organizations in children's early achievement are theoretically similar, leading to *Hypothesis 1: The greater the number of nonprofit organizations providing services, whether in competition with or in support of the public education system, the more that student performance will improve.*

Turning to issues of variability, one possibility is that nonprofit interactions with public schools could be more successful (i.e., associated with higher achievement) in some subject areas over others. Previous research from many fields has found substantial differences between the impacts of a host of independent variables (e.g., cash incentives, NCLB, social capital, etc.) and student achievement across academic subjects like math, reading, and science (Bettinger 2012; Dee and Jacob 2010; Leana and Pil 2006; McKown and Weinstein 2002; Stevenson, Schiller, and Schneider 1994). Reading is a subject of intense focus in the early childhood education years and in the primary grades of elementary school (Sénéchal and Young, 2008; Armbruster, Lehr, and Osborn 2001; Snow, Burns, and Griffin 1998; Mason 1980). Any nonprofit community partner working with schools should also be attuned to the importance placed on reading and therefore may be more focused on improving children's language and literacy skills rather than their development of math skills. The documented success of one-on-one reading interventions may also contribute to nonprofits focusing on reading interventions specifically (Ritter, Barnett, Denny and Albin 2009; Invernizzi, Rosemary, Juel and Richards, 1997). These potential motivating factors lead to *Hypothesis 2: The presence of nonprofits will be more strongly associated with children's reading achievement than with their math achievement.*

Another potential source of variability concerns timing within the transition into elementary school. The first component of this transition is how school ready children are; in other words, what level of academic skills they bring into formal schooling at the start of the kindergarten year and their early childhood trajectory of learning up to that point. The second component concerns what happens to children once school starts; in other words, what skills are gained in relation to their initial level of school readiness across the kindergarten year, indicating what their future learning trajectories are likely to be (Crosnoe, Bonazzo, and Wu 2015). The skill begets skills perspective posits a highly cumulative process of learning that prioritizes the value of early intervention (see Heckman 2000). This argument, and supporting evidence of the potentially high returns to early childhood interventions, suggests the value of taking action to promote the human capital development of children before the start of school. One reason is that who attends early childhood education programs (which are voluntary and often expensive) varies far more widely than who attends school (which is mandatory and free), so that interventions targeting these early years have potential to even out basic issues of access and opportunity (Duncan and Magnuson 2013; Shonkoff and Phillips 2000). Thus, I pose *Hypothesis 3: The presence of nonprofits will be more strongly associated with academic achievement around kindergarten entry than during the kindergarten year.*

A final source of variability concerns the difference between overall performance levels and sociodemographic disparities in performance. Major educational policies typically target both—improving how much all students learn while also reducing disparities in rates of learning across groups. To do both, a policy would need to facilitate skill development across the board but more so for traditionally disadvantaged groups than more advantaged groups. Although not always borne out in reality, the theoretical argument for this two-pronged philosophy is that the infusion of resources and supports will matter more to students who have few resources overall or would make more of a difference to them than they would for fellow students for whom multiple resources are redundant. Thus, the child experiencing disadvantage and the child with advantages both move ahead, with the former closing some of the distance on the latter in the process (Crosnoe and Benner 2015; Ceci and Papierno 2005; Arum 2000). This dual philosophy is central to the policies surrounding K-12 schooling, such as No Child Left Behind, while reducing disparities has been more in the spotlight in the recent push to support the expansion of early childhood education (Fuller 2007; Barnett and Belfield 2006). Given the importance of reducing disparities in the transition into school years, determining if nonprofits coincide with a reduction in disparities across groups is a crucial goal. Following this logic, I propose *Hypothesis 4: The presence of nonprofit organizations* *will be most strongly associated with academic achievement of children from low-income families.*

Testing these hypotheses within the general systems conceptual model in Figure 1 is important because of the extant lack of consideration of the impact of nonprofit organizations on a national level. Incorporating nonprofits into the theoretical models of community systems in which families, children, and schools are located could provide valuable insight into potential mechanisms to improve student achievement and reduce systemic disparities, helping to translate sociological research into policy action.

## Methods

### *Data*

The two sources of nationally representative child-level data used in this study were both collected by the National Center for Education Statistics (NCES). First, ECLS-B (see Snow et al. 2007) is a nationally representative sample of 10,700 children born in the U.S. in 2001 who were followed from nine months through kindergarten entry (2006 or 2007). Data were collected in multiple ways, including interviews with parents, caregivers, and teachers and direct assessments of children. The analytical sample used here included all children who participated in the age 4 and kindergarten waves who had direct assessments and zip code information ($n$ = 6,320; note, per NCES reporting requirements, all sample sizes are rounded to the nearest 10). Second, ECLS-K is a nationally representative cohort of over 21,000 children enrolled in approximately 1,000 schools in 1998 (Rathbun and West 2004). The multistage sampling frame began with 100 primary sampling units comprising counties and county groups from which schools were sampled, with approximately 23 students from each school selected (West, Denton, and Reaney 2000). ECLS-K also includes data from interviews with parents and direct assessments of children. The analytical sample used here included all children who participated in both kindergarten waves who had zip code information (*n* = 16,460).

For both data sets, I included all available data on children whether they attended public or private school in kindergarten. This inclusion maintained the representativeness of the sample, maximized sample size, and allowed the nonprofit results to be generalizable to all U.S. children. Given my conceptual focus on public education, however, I controlled for school sector and also did a comparative analyses for the public school subsample (*n* = 5,400 ECLS-B; *n* = 12,840 ECLS-K), which, not surprisingly, revealed that this large subsample drove the results reported for the full sample when controlling for school sector.

As explained below, longitudinal sampling weights accounted for differential attrition across waves in both data sets, and missing data estimation retained all cases within the two analytical samples. Finally, the zip code-level data to be merged into these two child-level data sets came from the Master File of nonprofit data from the NCCS, a cumulative list of all exempt organizations from 1989 to present and consists of over 2.5 million nonprofits, their addresses, years nonprofit status was received, and latest tax filing years.

*Measures*

*Children's achievement.* ECLS-B and ECLS-K assessed children in reading and math using individually administered two-stage adaptive tests, with content areas and domains based on the National Assessment of Educational Progress framework (NCES 2001). Used here are Item Response Theory (IRT) scale scores, which estimate patterns of responses for questions based on patterns of right, wrong, and omitted responses and on item parameters of difficulty, discriminating ability, and “guess-ability” (Rock and Pollack 2002). The two surveys were designed to have comparable measures. More information about the measurements can be found in the codebook (NCES, 2001) and a report from Rock and Pollack (2002). In ECLS-B, I used the test scores from kindergarten entry point as the dependent variable and the test scores from the prior pre-kindergarten wave as a lagged independent variable. In ECLS-K, I used the test scores from the spring of kindergarten and the fall of kindergarten in the same way. Descriptive statistics for these test scores (and all other variables) are presented in Table 1.

*Community nonprofit composition.* Three variables captured the total number of nonprofits (categorized by their NTEE codes) that were registered in a community area, defined through mapping software as a zip code and its contiguous neighbors. These community areas were also used to construct some other variables listed below. Competitors consisted of registered nonprofit preschools, primary, and elementary schools as well as elementary charter schools in a child’s community area. The second two variables are subsets of the supporter category. The variable for interveners counts all nonprofit educational services, remedial reading, and encouragement organizations as well as all parent teacher groups in the community area. The variable for youth developers counts supportive nonprofit organizations listed under NTEE code “O” for Youth Development such as youth centers and clubs, adult and child matching programs, and scouting organizations. All counts include only nonprofits that began operation before the survey data was collected. Using the NTEE codes in this way should also accomplish the goal of focusing on nonprofit organizations that likely serve the communities in which they are situated.

*Community socioeconomic status*. Because of the strong link between the socioeconomic composition of communities and children's academic indicators as well as theoretical links between community SES and nonprofit concentration, I assessed the socioeconomic status of each zip code with a composite of three standardized items (see Leventhal and Brooks-Gunn 2000): the percent of individuals in the area with a master's degree and above, the percent classified as professionals, and a dichotomous indicator signaling if the average household income for the zip code was twice the median household income of the entire sample ($\alpha$ = 0.76 in ECLS-B and 0.80 in ECLS-K).

*Other covariates.* A number of factors were taken into account to deal with various confounds related to selection into neighborhoods, nonprofit concentration, and children's achievement. Community covariates include urbanicity (1 = urban), region (1 = south), total number of children 6 and under in the community area, and the total number of square miles of that area. Family covariates include parent education (1 = highest level of parent education in household is less than high school and 5 = beyond a bachelor's degree), and low income (1 = total household income at 185% of the federal poverty line for household size or lower). Child covariates included center or preschool enrollment in the year before kindergarten (1 = enrolled), age in months, gender (1 = female), and race (dichotomous indicators for African American, Hispanic, and Other).

School and assessment covariates include sector (1 = public), timing of assessment (in days from first assessment date), and language of assessment (1 = Spanish). Additionally, in models for the kindergarten year, school covariates include Title 1 receipt (1 = yes), percent minority students (0-100), and school size (1 = 0-149, to 5 = 750 or more).

*Plan of Analysis*

The four hypotheses were tested in a series of regression models predicting test scores at time *t* by test scores at time *t*-1 (creating a lagged modeling structure effectively reducing endogeneity and capturing gains in scores over time; see Glazerman, Levy, and Myers 2003) and the focal community-level nonprofit predictors, with covariates and interactions of the nonprofit variables with low-income status added iteratively. The equation for these models is:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_5 + \ldots + \beta_k X_k + e_i$$

Models were estimated for each subject area and, within these subjects, for the period encompassing kindergarten entry (pre-kindergarten wave to the start of kindergarten in ECLS-B) and for the period encompassing the full kindergarten year (fall of kindergarten wave to the spring of kindergarten wave in ECLS-K). For each child, therefore, $Y_i$ successively represented the kindergarten math and reading score (ECLS-B) and the spring kindergarten math and reading score (ECLS-K). $\beta_1$ represented the effect of the logged number of competitor nonprofits in a child's community area on the test score of interest ($X_{1i}$), $\beta_2$ represented the effect of the number of interveners ($X_{2i}$), and $\beta_3$ represented the effect of the number of youth developers ($X_{3i}$). $\beta_4$ is the effect of the previous test score ($X_{4i}$)—prekindergarten score in ECLS-B, fall kindergarten math score in ECLS-K. Finally, $\beta_5 X_5 \ldots \beta_k X_k$ represented all additional covariates, with $\beta_0$ as the intercept. Due to the potential diminishing returns of the number of nonprofits for children's learning (i.e., moving from 0 nonprofits to 1 nonprofit is likely more meaningful than moving from 20 to 21), all nonprofit variables were logged (after 0.5 was added to each variable to avoid taking the log of zero). Logging changed the interpretation of the coefficients of interest, so that a one percent increase in the total number of nonprofits would correspond to an increase or decrease in the gain in a child's test scores of $\beta/100$.

In order to preserve as much data as possible, missing data were accounted for through *mvn* multiple imputation in STATA. Given the nested nature of the data (with children nested within schools within communities), I estimated multilevel models that explicitly partitioned variances into within- and between-level components. Doing so did returned no statistically significant improvement of model fit and yielded no substantively different results than a simpler method of using STATA's survey commands to account for the nesting of the data and produce robust standard errors. Given this lack of difference, the results presented here come from the simpler and more straightforward STATA approach. Finally, all models include longitudinal sampling weights to account for cross-wave attrition and to correct for other study design effects (e.g., the unequal probability of selection into the sample).

## Results

As a starting point, Table 2 presents the mean math and reading test scores for children in each subject in each time period according to the number of nonprofits in their communities. To ease interpretation, the number of nonprofits in a community has been trichotomized (0, 1-5, 5+) for these descriptive statistics, with significant differences between the latter two categories and the first category (calculated with *t* statistics) noted in the table. During the period encompassing kindergarten entry in ECSL-B, the mean math test score and the mean reading test score increased as the number of nonprofits (all categories) increased. During the kindergarten year in ECLS-K, only the mean reading test score consistently increased in tandem with the number of non-profits (and note that the math score actually slightly decreased as the number of youth developer nonprofits increased). Thus, descriptively, the presence of nonprofits in a community did seem to be associated with children's achievement in that community, with more consistency up to school entry rather than after school entry and more consistency in reading than math.

*Community Nonprofits and Children's Math Test Scores*

Turning to the hypothesis testing, Table 3 presents the results of a series of regressions for math test scores by time period. For each time period, Model 1 included the focal nonprofit factors and the *t*-1 test score (to create the lagged structure gauging test score gains), with the full set of covariates added in Model 2, and interactions (nonprofit variables x family income status) in subsequent models. The Model 2 results indicate that one nonprofit factor—number of interveners—was associated with children's test scores ($b = .47$, $p < .05$) after all covariates were controlled. This significant coefficient indicated that students from communities with three intervener nonprofits would experience a test score gain 1.4 points greater than those in communities with no such nonprofits, an effect size equivalent to about 14% of a standard deviation in the school entry math test score distribution in the ECLS-B. This represents a relatively small effect size, especially compared to the effect sizes of the other covariates (see Appendix A). For the school entry period, none of the interactions of the nonprofit factors with family income status were significant at conventional ($p < .05$) levels for math (interaction results not included in the table).

The second panel of Table 3 includes the results for the period between the start and end of kindergarten. The fully controlled results in Model 2 indicated that no nonprofit factor significantly predicted math test score gains after school had begun, net of all covariates. Yet, the significant interaction between two nonprofit factors and family income status (Models 3 and 4) indicated that nonprofits did matter for this subject during this time period; they just mattered differently for specific segments of the population. While separate models for interactions between each nonprofit variable and family income were run, only models with significant interactions are displayed in Table 3 and Table 4. Models containing all interactions together returned similar results with slightly reduced statistical significance for both interactions and an additional statistically significant interaction for youth developer nonprofits for the school entry period. I present the individually additive models here because they more succinctly represent overall trends.

To interpret these significant interactions between the number of competitor nonprofits and family income ($b = .43$, $p < .001$) and between the number of youth developer nonprofits and family income ($b = .30$, $p < .05$), I graphed the predicted math test scores at the end of kindergarten for children who lived in communities with 0 nonprofits and those who lived in communities with three nonprofits (roughly one standard deviation above the mean for those counts), with all other variables in the model, including the prior test score, held to their sample means. These predicted scores are presented in Figures 2 and 3.

For both types of nonprofits, children from low-income families posted greater gains on the math test over time when living in communities with more nonprofits, and disparities in test scores between such children and their peers from more affluent families were smaller in those same communities. Technically, these two patterns both supported Hypothesis 4, which was that children from low-income families would benefit more from the presence of nonprofits. Yet, this seemingly similar pattern across two kinds of nonprofits subsumed important differences. The interaction between youth developer nonprofits and family income status was most clearly in the spirit of the hypothesis, as the closing of disparities between the two groups of children was due to the disadvantaged children gaining ground while they more advantaged children did not lose ground. As Figure 3 shows, children from low-income families gained nearly a point in communities with three youth developer nonprofits relative to similar children in communities with none. For children in more affluent families, however, the number of youth developer nonprofits was not associated with math test score gains.

The interaction between competitor nonprofits and family income status was not as closely aligned with the spirit of the hypothesis, as the narrowing of disparities was driven not so much by the gains of children from low-income families as by the losses of other children. As Figure 3 shows, children from families that were not low-income had lower test scores when living in communities with three competitor nonprofits than in communities with none (with an opposite, albeit less pronounced, pattern for the children from low-income families). As a result, test score disparities related to family income were actually reversed in communities with a greater presence of competitor nonprofits, but this reversal occurred because of gains by children from low-income families and losses by children who were not from low-income families.

Because these results were only for math, they do not speak to Hypothesis 2. In terms of Hypotheses 1, 3, and 4, they contain several relevant observations. First, they indicate some support for Hypothesis 1, notably that the number of intervener nonprofits was associated with slight increases in math scores, while the youth developer nonprofits were associated with increases for children from low-income families. Furthermore, specifying the type of nonprofit organization proved important for evaluating Hypothesis 1 because intervener organizations showed a positive association with student outcomes in general while youth developer and competitor nonprofits did not for the sample as a whole (with competitor nonprofits actually displaying a negative association with math gains for children not from low-income families). Hypothesis 3 was also partially supported by the fact that the only significant nonprofit association in the expected direction in models containing all controls occurred during the kindergarten entry period. Finally, I found qualified support for Hypothesis 4 in that children from low income families experienced stronger gains in test scores as the number of competitor and youth developer nonprofits in their communities increased compared to their peers not from low-income families. For competitor nonprofits, however, this positive trend for children from low-income families was coupled with a more negative trend for all other children.

*Community Nonprofits and Children's Reading Test Scores*

Table 4 presents the results of the same series of regressions for reading test scores. The fully controlled results from Model 2 in the kindergarten entry period revealed that no nonprofit factors were significantly associated with reading test scores. Model 2 for the kindergarten year period did display a significant association between the number of youth developer nonprofits and reading test scores ($b$ = .34; $p$ <.05). This significant coefficient indicated that the number of youth developer nonprofits was positively associated with reading test score gains in the kindergarten year, with another relatively small effect size. Children in communities with three such nonprofits as opposed to zero experienced a reading score gain of 1.03 points, an effect equivalent to about 10% of a standard deviation in the spring kindergarten math test score distribution in ECLS-K.

Model 3 for both the kindergarten entry and kindergarten year periods revealed two significant interactions of the nonprofit factors with family income status for this subject. For the kindergarten entry period, this interaction was between the number of youth developer nonprofits and family income ($b$ = -0.96, $p$ < .05) and, for the kindergarten year, it was between the number of intervener nonprofits and family income ($b$ = -.31, $p$ < .05). Again, to interpret these interaction terms, I graphed the predicted reading scores for children who lived in communities with 0 and three nonprofits, with all other variables, including the prior test scores, held to their sample means. These predicted scores are presented in Figures 4 and 5.

Although youth developer nonprofits were associated with gains overall for children in the kindergarten year period, children from low-income families in the ECLS-B did not experience gains in reading test scores across the transition into kindergarten when they lived in communities with greater numbers of youth developer nonprofits. Instead, their test score gains were weaker in communities with three such nonprofits than in communities with none, with the opposite (and slightly weaker) pattern for their peers from families that were not low-income. They did not appear to be more affected by the presence of youth developer nonprofits than other children, and they certainly did not appear to be more positively affected by this potential community resource. As a result, income-related disparities in children's reading test scores grew in tandem with the increase in this kind of nonprofit in the community. A similar pattern is also reflected in the interaction between family income and intervener nonprofits in ECLS-K, with children from low-income families experiencing no gains in scores from increased intervener nonprofits and children who were not from low-income families experiencing about a half a point increase in such communities.

Going back to the hypotheses, in addition to intervener nonprofits being associated with increased math test scores in the transition into kindergarten, they were also associated with increased reading test scores in the kindergarten year, (evidence for Hypothesis 1, mixed support for Hypotheses 2 and 3). No other nonprofit count was generally associated with reading or math test scores in the child population at large (evidence against Hypothesis 1). Finally, competitor and youth developer nonprofits were more closely associated with the kindergarten year math test scores of children from low-income families. Youth developer nonprofits at kindergarten entry and intervener nonprofits in the kindergarten year, however, were associated with increased reading score gains from children from families that were not low-income and actually associated with reduced reading score gains for children in low-income families (mixed support for Hypotheses 2 and 4).

## Conclusion

Nonprofit organizations are a potential mechanism through which interventions in education can be delivered, despite the fact that they are frequently left out of theoretical models concerning structural and contextual influences on student outcomes and educational disparities. The general goal of this research, therefore, was to investigate whether and how the composition of nonprofits in a community are associated with the outcomes of the community's children, a preliminary but necessary step in the consideration of the usefulness of school-community partnerships that have received so much public attention.

Consequently, I combined two sources of national data to test several hypotheses regarding nonprofit involvement in the educational system. I summarize those results here. Nonprofits appeared to play a diverse role in the achievement gains of some, but not all, students. For example, the community composition of nonprofit organizations was more consistently associated with gains on math tests for children from low-income families, but it was more consistently associated with reading gains for children from families that were not low-income. In terms of timing, links between nonprofit composition and children's test scores did not differ overall between the school entry period and the kindergarten year, but links between nonprofit composition and socioeconomic disparities in children's test scores did. Specifically, the presence of nonprofit organizations seemed to be associated with more optimal patterns of reductions in disparities (i.e., driven by gains among children from low-income families rather than by losses among other children) in in the kindergarten year period more than in the school entry period.

These results underscore three important themes. The first is the importance of investigating nonprofits according to the theoretically derived functions they may serve in a community. The differential test score gains experienced by children from low-income families and other children according to the presence of competitor and youth developer nonprofits serve to underscore the importance of understanding the heterogeneity of the nonprofit field – the very heterogeneity that has often been cited as a major challenge for research on the impact of such organizations. As new sources of data become available, understanding and exploiting this heterogeneity needs to be an explicit goal of research. In this study, for example, the presence of youth developer organizations (nonprofits with missions that would align more with the development of all youth in a community) was associated with less socioeconomic divergence in math test score gains while the presence of competitor nonprofit organizations (entities whose missions would necessarily align more with promoting the success of individuals actually enrolled in their programs) was not.

This point does highlight a limitation of this study: the fact that I cannot determine if individuals in the NCES data actually participated in nonprofit programs or not—data that I argue should be gathered in future surveys either at the student or school level. Similar to the motivation for including children from private schools in the sample, this data limitation does not interfere with my ability to consider the observable impact of nonprofit composition on the community as a whole. Furthermore, assessing the theoretical ability of nonprofit organizations to improve the outcomes of all individuals in a community—not just direct participants or clients—is one of the motivating factors behind calls for third sector investment beyond private businesses and the public services that are perceived to be failing. The very nature of nonprofits serving different communities at different levels of intervention and intensity necessitates more careful data collection directly from nonprofits and those they serve rather than indirectly from tax forms. For now, however, use of the NTEE codes to pair nonprofit organizations closer to their theoretical missions and the communities they serve represents a substantial move in this direction.

The second theme concerns the need for a deeper understanding of who is best served by which nonprofit organizations. This study revealed different associations between nonprofit measures and the math and reading gains of children from families of differing levels of income across all time periods. This variability is a challenge, but it also speaks to the reality of educational policy that one size rarely fits all. More targeted approaches are likely to be more effective. For example, if intervener and youth developer nonprofit organizations focus their attention more towards increasing the test score gains of children from low-income families, then they may see more of an impact from their services. A limitation of this study relevant to this conclusion is that it cannot explicitly speak to *how* to target this population or the precise ways to increase their achievement through nonprofit involvement. What it can do is point future studies to this possibility to better understand the details and mechanisms behind nonprofit composition and educational success.

The third theme speaks to issues concerning the association between nonprofit organizations and the socioeconomic statuses of the individuals who participate in that their programs. Two unexpected results indicate the importance of theorizing the different ways individuals from different family backgrounds may interact with nonprofit organizations. First, the presence of more competitor nonprofits was associated with increased school entry math scores for children from low-income families but a decrease in math scores for children not from low-income families during the same period. Second, when communities housed more intervener and youth developer nonprofit organizations, socioeconomic disparities in reading scores were wider. Perhaps these patterns reflect socioeconomic differences in how children and families—and the schools serving them—interact with nonprofits. Currently, the data are not there to examine these interactions, suggesting the need for qualitative data collection. Another possibility is selection—nonprofits clustering in areas that already have problems with disparities. New kinds of statistical approaches, such as instrumental variables, are needed to delve more deeply into this possibility.

Given the exponential increase in nonprofit organizations over the past twenty years, these types of non-governmental agencies will be involved in the lives of many people, especially children, in the years to come. If the sheer number of organizations or the quantity of money spent on them is not motivation enough, the logic of market competition suggests that they may be some of the most innovative organizations focusing their attention on alleviating educational problems and social ills more broadly. Building on this preliminary work to better situate nonprofits in theoretical frameworks of educational inequality and collecting the data to directly examine such frameworks, therefore, should be a goal of sociological research moving forward.

Appendix A

Table A1. Fully Controlled Models Predicting Math and Reading Score Gains

| | School Entry (ECLS-B) | | Kindergarten Year (ECLS-K) | |
|---|---|---|---|---|
| | Math | Reading | Math | Reading |
| Nonprofit Count | | | | |
| Competitors | -0.240 | -0.616+ | -0.054 | -0.055 |
| | (0.257) | (0.368) | (0.088) | (0.137) |
| Supporters | | | | |
| Interveners | 0.465* | 0.466 | -0.066 | -0.011 |
| | (0.211) | (0.311) | (0.084) | (0.132) |
| Youth developers | -0.059 | -0.051 | 0.118 | 0.343* |
| | (0.225) | (0.332) | (0.095) | (0.145) |
| Previous Score | 0.212*** | 0.181*** | 0.923*** | 0.563*** |
| | (0.019) | (0.024) | (0.011) | (0.018) |
| Low Income (1 = yes) | -2.043*** | -2.798*** | -0.313* | -1.793*** |
| | (0.383) | (0.583) | (0.122) | (0.164) |
| Community SES | 1.056*** | 1.017* | -0.164 | 0.072 |
| | (0.254) | (0.398) | (0.102) | (0.162) |
| Community Covariates | | | | |
| Urbanicity (1 = urban) | -0.192 | 0.798 | 0.134 | 0.005 |
| | (0.537) | (0.728) | (0.171) | (0.266) |
| Region (1 = south) | 0.020 | 2.030** | 0.656** | 1.256*** |
| | (0.377) | (0.624) | (0.234) | (0.336) |
| Total children | -0.000 | 0.000 | 0.000+ | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Total sqmi | -0.000 | -0.000 | 0.000 | 0.000** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Race | | | | |
| African American | -2.053*** | -0.661 | -1.419*** | -0.468 |
| | (0.471) | (0.651) | (0.228) | (0.297) |
| Hispanic | -2.586*** | -2.424*** | -0.260 | -2.686*** |
| | (0.458) | (0.625) | (0.206) | (0.358) |
| Other | -1.258 | -1.150 | 1.051*** | 0.556 |
| | (0.779) | (1.002) | (0.308) | (0.338) |

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1
Table continued on next page.

Table A1 (cont). Fully Controlled Models Predicting Math and Reading Score Gains

| | School Entry (ECLS-B) | | Kindergarten Year (ECLS-K) | |
|---|---|---|---|---|
| | Math | Reading | Math | Reading |
| Child Covariates | | | | |
| Parental education | 0.953*** | 1.699*** | 0.347*** | 1.209*** |
| | (0.097) | (0.140) | (0.058) | (0.082) |
| Gender (1 = female) | 0.293 | 1.509*** | -0.044 | 1.260*** |
| | (0.260) | (0.411) | (0.091) | (0.135) |
| Age | 0.607*** | 0.764*** | 0.033* | 0.151*** |
| | (0.036) | (0.048) | (0.013) | (0.017) |
| Center or preK | 0.615+ | 1.490** | 0.143 | 0.732*** |
| | (0.311) | (0.511) | (0.107) | (0.150) |
| Assessment Covariates | | | | |
| Language (1 = Spanish) | 27.512*** | 34.850*** | -1.908*** | 23.928*** |
| | (0.774) | (4.302) | (0.284) | (0.916) |
| Timing | 0.018*** | 0.044*** | 0.024*** | 0.018** |
| | (0.004) | (0.007) | (0.005) | (0.006) |
| School Covariates | | | | |
| Sector (1 = public) | -1.414*** | -0.615 | -0.088 | -1.035** |
| | (0.404) | (0.685) | (0.236) | (0.379) |
| Title1 (1 = yes) | | | -0.001 | -0.209 |
| | | | (0.149) | (0.240) |
| Size | | | 0.099 | 0.034 |
| | | | (0.081) | (0.119) |
| Minority representation | | | -0.004 | -0.011** |
| | | | (0.003) | (0.004) |
| Constant | -7.526** | -25.185*** | 4.896*** | 4.706** |
| | (2.637) | (3.576) | (1.017) | (1.549) |
| Pseudo $R^2$ | 0.357 | 0.323 | 0.592 | 0.612 |
| Observations | 6,320 | 6,320 | 16,460 | 16,460 |

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 1. Descriptive Statistics for Prekindergarten and Kindergarten Data

| | ECLS-B | | | | | ECLS-K | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Obs | Mean | Std. Dev. | Min | Max | Obs | Mean | Std. Dev. | Min | Max |
| Dependent Variables | | | | | | | | | | |
| Math | 6610 | 44.14 | 10.45 | 10.85 | 69.69 | 17310 | 27.72 | 8.87 | 7.44 | 59.34 |
| Reading | 6600 | 44.68 | 14.78 | 12.39 | 82.48 | 16580 | 32.14 | 10.05 | 11.00 | 70.80 |
| Endogeneity Control | | | | | | | | | | |
| Previous math | 6340 | 29.38 | 10.07 | 9.87 | 65.74 | 17120 | 19.61 | 7.38 | 6.65 | 59.82 |
| Previous reading | 6360 | 25.53 | 10.64 | 11.65 | 80.29 | 16120 | 22.26 | 7.85 | 10.08 | 60.00 |
| Nonprofit Counts | | | | | | | | | | |
| Competitors | 6670 | 10.64 | 9.27 | 0.00 | 65.00 | 17490 | 7.96 | 7.70 | 0.00 | 68.00 |
| Supporters | | | | | | | | | | |
| Interveners | 6670 | 38.78 | 51.05 | 0.00 | 1098.00 | 17490 | 35.10 | 61.11 | 0.00 | 1084.00 |
| Youth developers | 6670 | 5.42 | 5.18 | 0.00 | 76.00 | 17490 | 3.92 | 4.31 | 0.00 | 40.00 |
| Community Covariates | | | | | | | | | | |
| Community SES | 6680 | 0.00 | 0.79 | -1.41 | 6.34 | 17500 | 0.00 | 0.85 | -1.48 | 4.06 |
| Urbanicity (1 = urban) | 6560 | 0.83 | 0.38 | 0.00 | 1.00 | 17500 | 0.42 | 0.49 | 0.00 | 1.00 |
| South | 6680 | 0.36 | 0.48 | 0.00 | 1.00 | 17500 | 0.32 | 0.47 | 0.00 | 1.00 |
| Children (6 and under) | 6680 | 10510.16 | 8950.36 | 0.00 | 70895.00 | 17500 | 9939.85 | 8126.53 | 0.00 | 62892.00 |
| Square miles | 6670 | 764.17 | 1816.08 | 0.00 | 65362.15 | 17490 | 642.15 | 1347.73 | 0.00 | 22210.83 |
| Child Covariates | | | | | | | | | | |
| Parental education | 6670 | 5.01 | 2.05 | 1.00 | 9.00 | 17170 | 2.94 | 1.17 | 1.00 | 5.00 |
| Low income | 6680 | 0.44 | 0.50 | 0.00 | 1.00 | 17500 | 0.39 | 0.49 | 0.00 | 1.00 |
| Center or preK | 6640 | 0.96 | 1.00 | 0.00 | 4.00 | 16820 | 0.58 | 0.49 | 0.00 | 1.00 |
| Age (months) | 6680 | 68.63 | 4.74 | 57.20 | 86.00 | 17490 | 68.46 | 4.46 | 45.77 | 96.50 |
| Gender (1 = female) | 6680 | 0.50 | 0.50 | 0.00 | 1.00 | 17500 | 0.49 | 0.50 | 0.00 | 1.00 |

Table continued on next page.

Table 1. (Continued). Descriptive Statistics for Prekindergarten and Kindergarten Data

| | ECLS-B | | | | | ECLS-K | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Obs | Mean | Std. Dev. | Min | Max | Obs | Mean | Std. Dev. | Min | Max |
| Child Covariates | | | | | | | | | | |
| Race | | | | | | | | | | |
| White | 6670 | 0.41 | 0.49 | 0.00 | 1.00 | 17470 | 0.57 | 0.50 | 0.00 | 1.00 |
| African American | 6670 | 0.16 | 0.36 | 0.00 | 1.00 | 17470 | 0.15 | 0.35 | 0.00 | 1.00 |
| Hispanic | 6670 | 0.20 | 0.40 | 0.00 | 1.00 | 17470 | 0.18 | 0.38 | 0.00 | 1.00 |
| Other | 6670 | 0.12 | 0.33 | 0.00 | 1.00 | 17470 | 0.11 | 0.32 | 0.00 | 1.00 |
| Assessment Covariates | | | | | | | | | | |
| Language (1 = Spanish) | 6651 | 0.00 | 0.02 | 0.00 | 1.00 | 17500 | 0.04 | 0.18 | 0.00 | 1.00 |
| Timing (in days) | 6680 | 79.84 | 49.49 | 15.00 | 530.00 | 17500 | 65.98 | 16.45 | 8.00 | 128.00 |
| School Covariates | | | | | | | | | | |
| Sector (1 = public) | 6450 | 0.88 | 0.33 | 0.00 | 1.00 | 17500 | 0.79 | 0.41 | 0.00 | 1.00 |
| Title 1 receipt (1 = yes) | | | | | | 15030 | 0.60 | 0.49 | 0.00 | 1.00 |
| Size | | | | | | 17330 | 3.29 | 1.16 | 1.00 | 5.00 |
| Percent minority | | | | | | 17070 | 38.24 | 35.10 | 0.00 | 100.00 |

Table 2. Mean IRT Scores by Number of Nonprofits by Group

| | Mean IRT Score (*SD*) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | School Entry (ECLS-B) | | | | | | Kindergarten Year (ECLS-K) | | | | | |
| Number of Nonprofits | 0 | | 1 to 5 | | 5+ | | 0 | | 1 to 5 | | 5+ | |
| Math | | | | | | | | | | | | |
| Competitors | 41.65 | -10.14 | 43.30* | -10.14 | 44.76* | -10.56 | 27.39 | -8.5 | 27.61 | -8.73 | 27.64 | -9.01 |
| Supporters | | | | | | | | | | | | |
| Interveners | 42.41 | -9.54 | 42.69 | -10.09 | 44.39* | -10.51 | 27.35 | -8.51 | 27.56 | -8.73 | 27.63 | -8.9 |
| Youth developers | 43.15 | -9.98 | 43.97* | -10.31 | 44.65* | -10.76 | 27.4 | -8.84 | 28.04* | -8.89 | 26.90* | -8.79 |
| Reading | | | | | | | | | | | | |
| Competitors | 42.52 | -12.82 | 43.39 | -14.15 | 45.45* | -15.21 | 31.28 | -9.85 | 31.66 | -9.9 | 32.42* | -10.16 |
| Supporters | | | | | | | | | | | | |
| Interveners | 41.7 | -13.42 | 42.87 | -13.33 | 45.00* | -15.01 | 30.58 | -9.79 | 31.23 | -9.79 | 32.23* | -10.09 |
| Youth developers | 43.53 | -14.05 | 44.45+ | -14.47 | 45.27* | -15.41 | 31.35 | -10.21 | 32.29* | -9.98 | 31.99* | -10.05 |

* $p < 0.05$, + $p < 0.1$ for differences between 0 and 1 to 5 and 0 and 5+.

Table 3. Results of Models Predicting Math Scores by Nonprofit Count

| | β Coefficients (SE) | | | | | |
|---|---|---|---|---|---|---|
| | School Entry (ECLS-B) | | Kindergarten Year (ECLS-K) | | | |
| | (1) | (2) | (1) | (2) | (3) | (4) |
| Nonprofit Count | | | | | | |
| Competitors | 0.256 | -0.240 | -0.107 | -0.054 | -0.240* | -0.055 |
| | (0.281) | (0.257) | (0.087) | (0.088) | (0.099) | (0.087) |
| Supporters | | | | | | |
| Interveners | -0.073 | 0.465* | -0.066 | -0.066 | -0.065 | -0.067 |
| | (0.225) | (0.211) | (0.076) | (0.084) | (0.082) | (0.083) |
| Youth developers | -0.312 | -0.059 | 0.122 | 0.118 | 0.117 | -0.009 |
| | (0.253) | (0.225) | (0.091) | (0.095) | (0.094) | (0.096) |
| Previous Math | 0.260*** | 0.212*** | 0.977*** | 0.923*** | 0.923*** | 0.923*** |
| | (0.022) | (0.019) | (0.010) | (0.011) | (0.011) | (0.010) |
| Low Income (1 = yes) | | -2.043*** | | -0.313* | -0.981*** | -0.590*** |
| | | (0.383) | | (0.122) | (0.203) | (0.149) |
| Family Income Interactions | | | | | | |
| Competitors x low income | | | | | 0.428*** | |
| | | | | | (0.127) | |
| Youth developers x low income | | | | | | 0.299* |
| | | | | | | (0.133) |
| Constant | 36.740*** | -7.526** | 9.023*** | 4.896*** | 5.220*** | 5.020*** |
| | (0.823) | (2.637) | (0.306) | (1.017) | (1.017) | (1.025) |
| Pseudo $R^2$ | 0.149 | 0.357 | 0.576 | 0.592 | 0.593 | 0.593 |
| *N* | 6,320 | 6,320 | 16,460 | 16,460 | 16,460 | 16,460 |

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Note: Models 2 and 3 contain controls for community SES, urbanicity, south, total children in zipcode area, total squaremiles in zipcode area, parental education ,poverty status, center or prek care, gender of child, race of child, age of child, public/private school, assessment timing, and language of assessment; as well as Title 1 receipt, school size, and percent school minority representation for ECLS-K models

Table 4. Results of Models Predicting Reading Scores by Nonprofit Counts

| | β Coefficients (SE) | | | | | |
|---|---|---|---|---|---|---|
| | School Entry (ECLS-B) | | | Kindergarten Year (ECLS-K) | | |
| | (1) | (2) | (3) | (1) | (2) | (3) |
| Nonprofit Count | | | | | | |
| Competitors | 0.023 | -0.616+ | -0.582 | 0.044 | -0.055 | -0.052 |
| | (0.383) | (0.368) | (0.367) | (0.136) | (0.137) | (0.137) |
| Supporters | | | | | | |
| Interveners | 0.331 | 0.466 | 0.467 | -0.034 | -0.011 | 0.121 |
| | (0.346) | (0.311) | (0.307) | (0.134) | (0.132) | (0.144) |
| Youth developers | -0.542 | -0.051 | 0.353 | 0.105 | 0.343* | 0.346* |
| | (0.388) | (0.332) | (0.350) | (0.154) | (0.145) | (0.145) |
| Previous Reading | 0.215*** | 0.181*** | 0.182*** | 0.757*** | 0.563*** | 0.564*** |
| | (0.029) | (0.024) | (0.024) | (0.018) | (0.018) | (0.018) |
| Low Income (1 = yes) | | -2.798*** | -1.541+ | | -1.793*** | -0.919* |
| | | (0.583) | (0.871) | | (0.164) | (0.380) |
| Family Income Interactions | | | | | | |
| Interveners x low income | | | | | | -0.305* |
| | | | | | | (0.129) |
| Youth developers x low income | | | -0.958* | | | |
| | | | (0.433) | | | |
| Constant | 38.523*** | -25.185*** | -25.777*** | 14.934*** | 4.706** | 4.282** |
| | (1.135) | (3.576) | (3.517) | (0.546) | (1.549) | (1.553) |
| Pseudo $R^2$ | 0.102 | 0.323 | 0.324 | 0.531 | 0.612 | 0.612 |
| *N* | 6,320 | 6,320 | 6,320 | 16,460 | 16,460 | 16,460 |

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Note: Models 2 and 3 contain controls for community SES, urbanicity, south, total children in zipcode area, total squaremiles in zipcode area, parental education ,poverty status, center or prek care, gender of child, race of child, age of child, public/private school, assessment timing, and language of assessment; as well as Title 1 receipt, school size, and percent school minority representation for ECLS-K models

Figure 1: Influences on Child Outcomes during the Transition to School

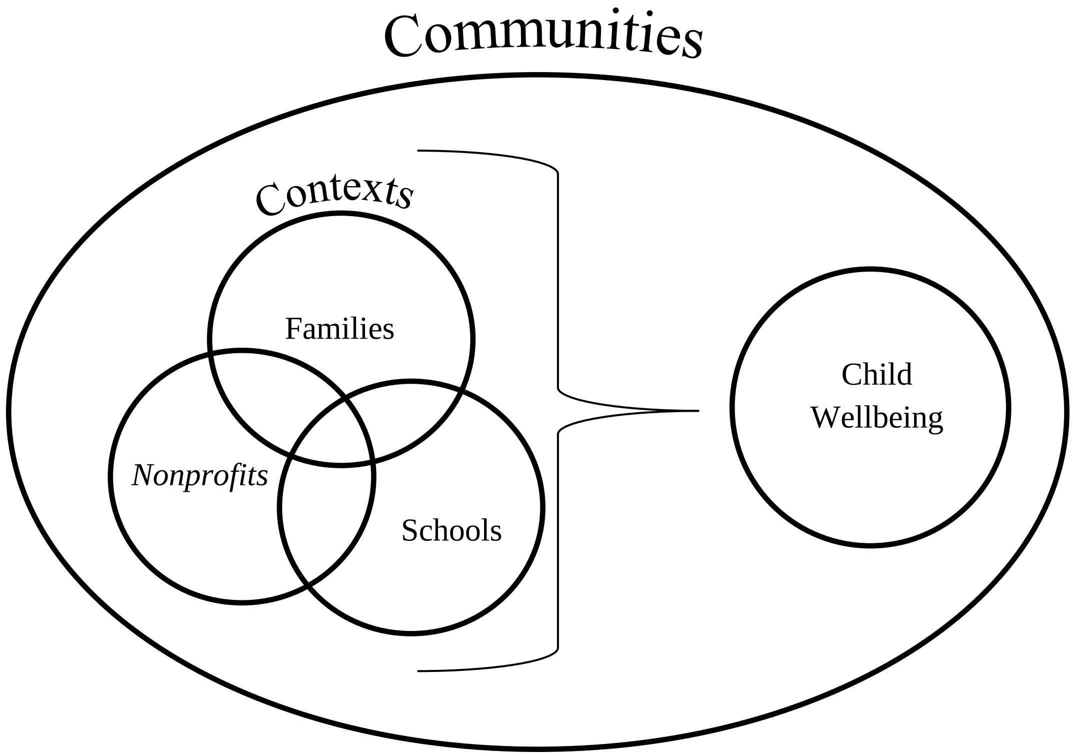


Figure 2. Predicted Kindergarten Math Test Scores in ECLS-K, by Competitor Nonprofits and Family Income

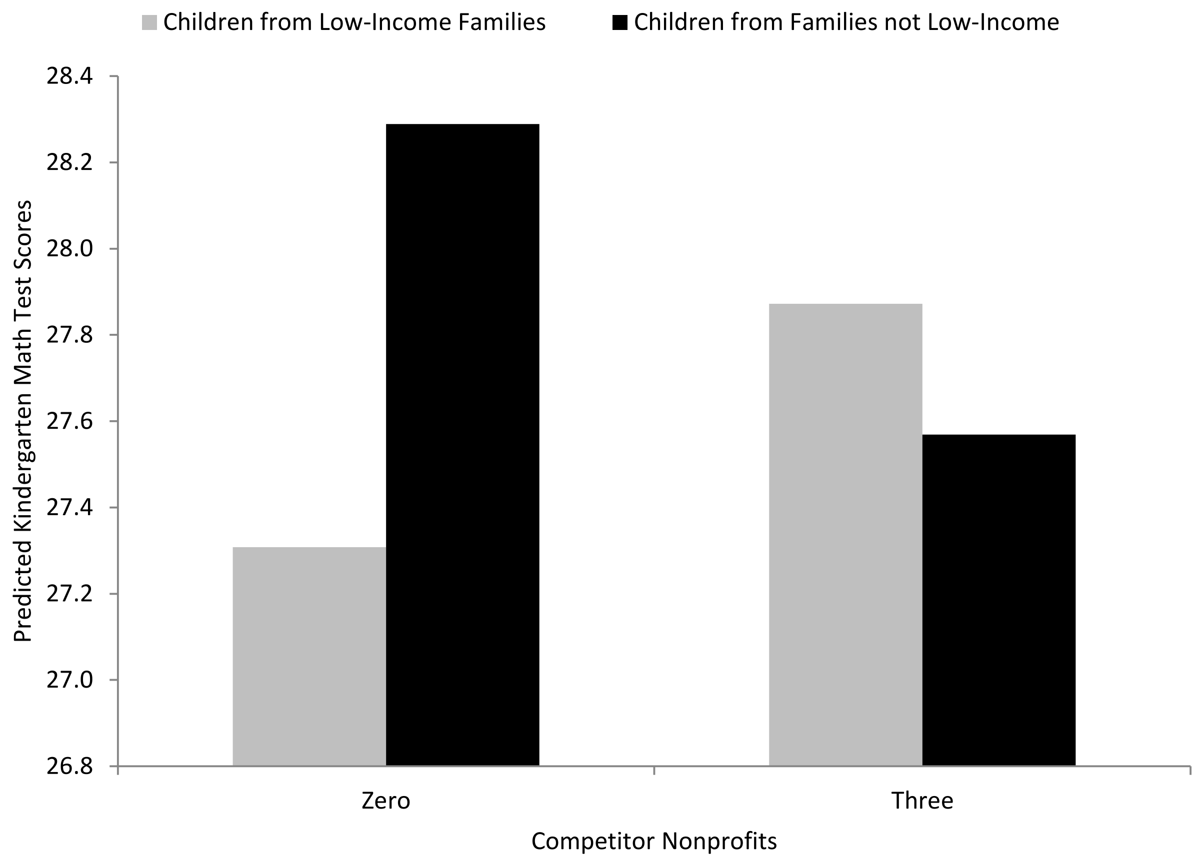


Figure 3. Predicted Kindergarten Math Test Scores in ECLS-K, by Youth Developer Nonprofits and Family Income

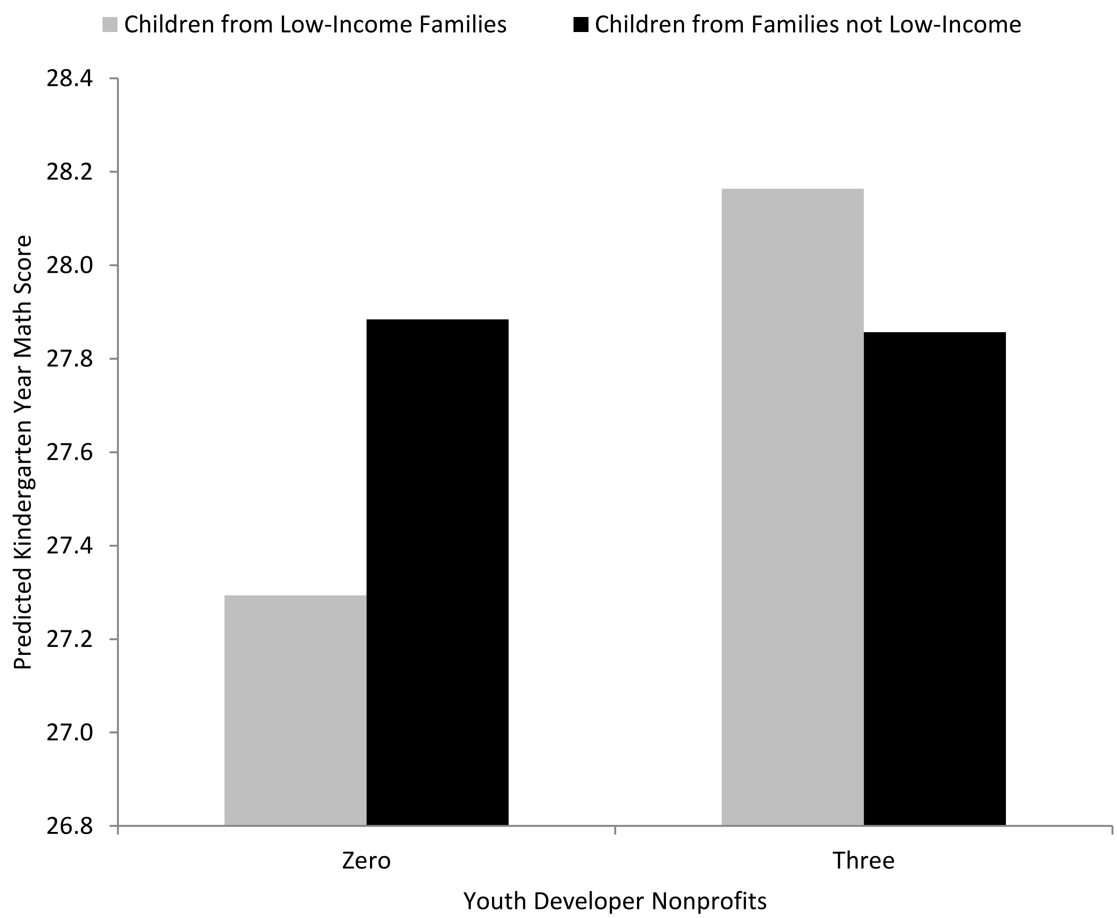


Figure 4. Predicted School Entry Reading Test Scores in ECLS-B, by Youth Developer Nonprofits and Family Income

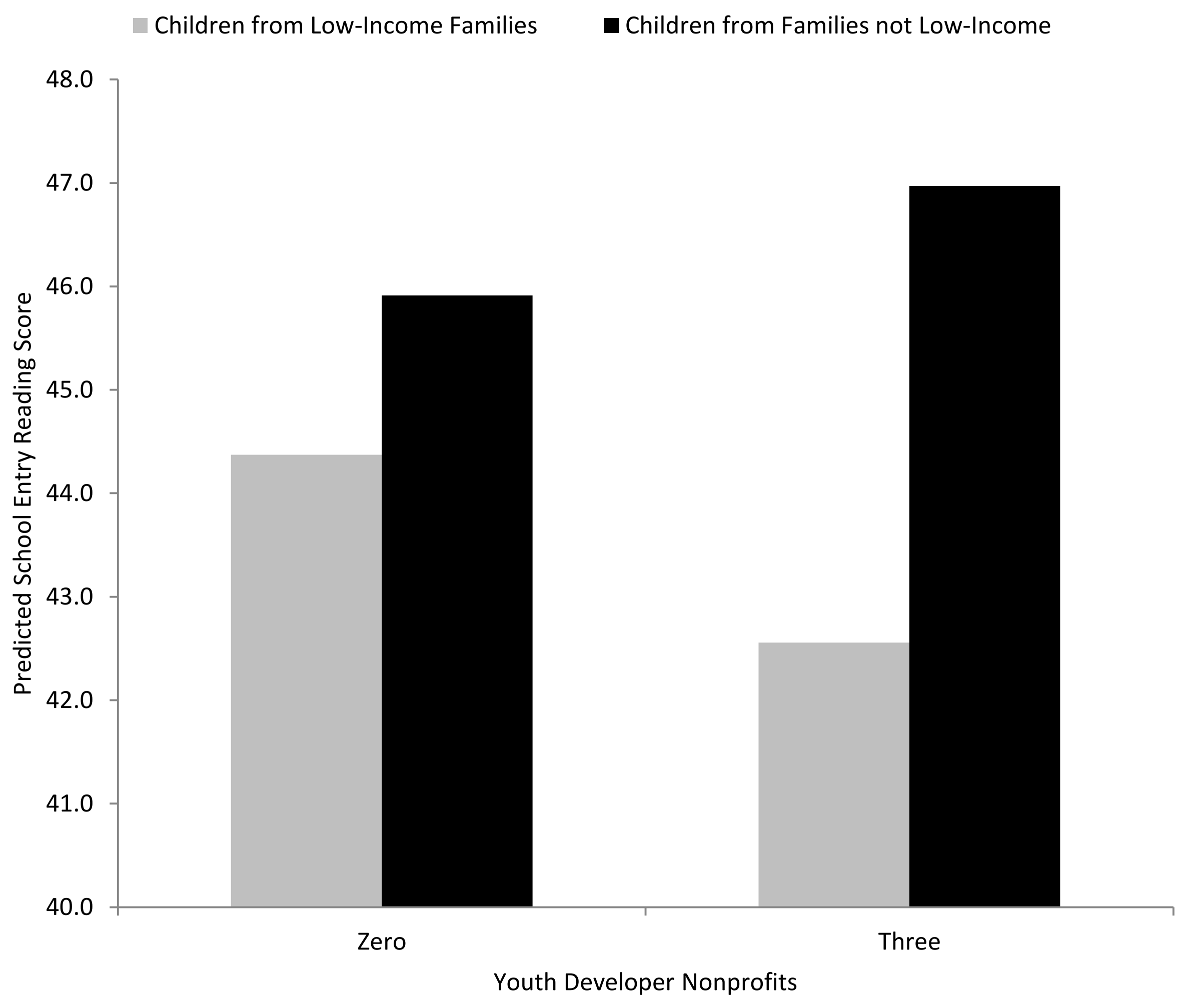
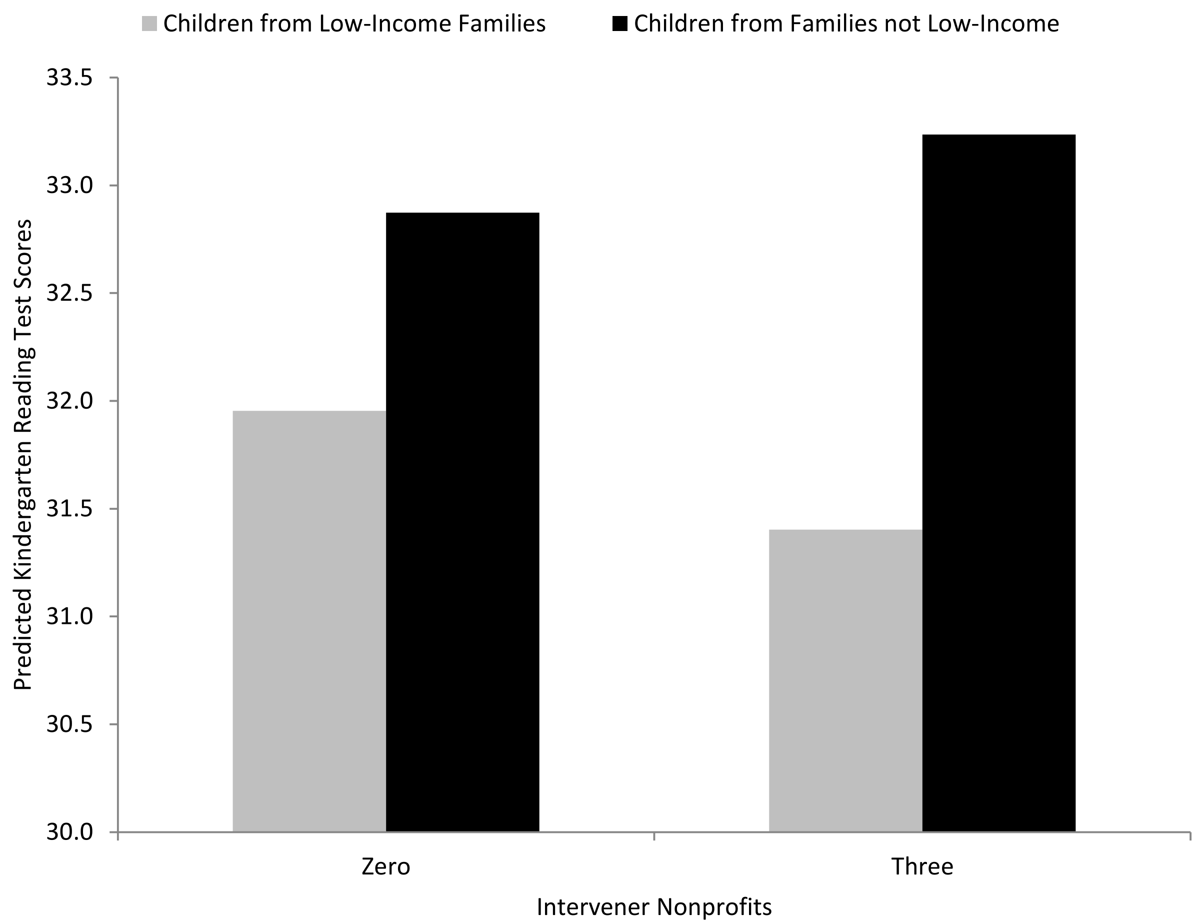


Figure 5. Predicted Kindergarten Reading Test Scores by Intervener Nonprofits and Family Income



References

Alexander, Karl L., Dorris R. Entwisle and Linda S. Olson. 2007. “Lasting consequences of the summer learning gap,” *American Sociological Review*.  72(2): 167-180.

Allard, Scott W. 2009. *Out of Reach: Place, Poverty, and the New American Welfare State.* New Haven, CT: Yale University

Altonji, Joseph G., and Richard K. Mansfield. 2011. "The Role of Family, School, and Community Characteristics in Inequality in Education and Labor-Market Outcomes." Pp. 339-58 in *Whither Opportunity? Rising Inequality, Schools, and Children's Life Chances* edited by Greg J. Duncan and Richard Murnane. New York: Russell Sage Foundation.

Anheier, Helmut K. 1954. *Nonprofit Organizations: An Introduction: Theory, Management, Policy.* New York, NY: Routledge.

Armbruster, Bonnie B., Fran Lehr, and Jean Osborn. 2001. *Put reading first: the research building blocks for teaching children to read : kindergarten through grade 3*. Washington, D.C.: National Institute for Literacy, National Institute of Child Health and Human Development, U.S. Dept. of Education

Arum, Richard. 2000. "Schools and Communities: Ecological and Institutional Dimensions," *Annual Review of Sociology.* 26:395-418.

Barnett, Steven W. and C. R. Belfield. 2006. “Early Childhood Development and Social Mobility.” *The Future of Children*, 16(2): 73-98

Bates, Littisha A. and Jennifer Glick. 2013. “Does it Matter if Teachers and Schools Match the Student? Racial and Ethnic Disparities in Problem Behaviors.” *Social Science Research,* 42(5), 1180-1190.

Bertalanffy, Ludwig von. 1969. *General system theory: foundations, development, applications.* New York, NY: G. Braziller.

Bettinger, Eric P. 2012. “Paying to Learn: The Effect of Financial Incentives on Elementary School Test Scores.” *The Review of Economics and Statistics,* 94(3): 686-698

Bielefeld, Wolfgang. 2000. “Metropolitan Nonprofit Sectors: Findings from NCCS Data.” *Nonprofit and Voluntary Sector Quarterly,* 29(2): 297-314

Ceci, Stephen J. and Paul B. Papierno. 2005. “When the “Have-Nots” Gain but the “Haves” Gain Even More.” *American Psychologist,*60(2): 149-160.

Crosnoe, Robert and Aprile Benner. (in press). “Children at School.” In *Handbook of Child Psychology and Developmental Science, Vol. 4: Ecological Settings and Processes,* edited by Marc Bornstein & Tama Leventhal (series editor: Richard M. Lerner). New York, NY: Wiley

Crosnoe, Robert, Claude Bonazzo, and Nina Wu. (in press). *Healthy Learners: Poverty, Immigration, and Opportunity in Early Childhood Education.* New York, NY: Teachers College Press.

Darensbourg, Alicia M. and Jamilia J. Blake. 2014. “Examining the Academic Achievement of Black Adolescents: Importance of Peer and Parental Influences.” *Journal of Black Psychology,* 40(2), 191-212.

Dee, Thomas and Brian Jacob. 2010. “Evaluating NCLB: Accountability has Produced Substantial Gains in Math Skills but not in Reading.” *Education Next,* 10(3): 54

Duncan, Greg J and Richard J Murnane. 2014. “Growing Income Inequality Threating American Education: Rising Economic and Social Inequality has Weakend Neighborhoods and Families in Ways that Make Effective School Reform More Difficult” *Phi Delta Kappan*. 95(6): 8.

Duncan, Greg J. and Katherine Magnuson. 2013. “Investing in Preschool Programs.” *The Journal of Economic Perspectives,* 27(2): 109-132.

Fuller, Bruce. 2007. *Standardized Childhood: The Political and Cultural Struggle over Early Education.* Stanford, CA: Stanford University Press.

Garrett, Thomas and Russell Rhine. 2010. “Government Growth and Private Contributions to Charity.” *Public Choice,* 143(1/2): 103-120.

Glazerman, Steven, Dan Levy, and David. Myers. 2000. “Nonexperimental versus experimental estimates of earnings impacts,” *Annals of the American Academy of Political and Social Science,* 589: 63-85.

Heckman, James J. 2006. “Skill Formation and the Economics of Investing in Disadvantaged Children.” *Science*, 312(5782):1900-1902.

Heckman, James J. 2000. “Policies to Foster Human Capital.” *Research in Economics,* 54(1): 3-56.

Invernizzi, Marcia, Catherine Rosemary, Connie Juel and Herbert C. Richards. 1997. “At-Risk Readers and Community Volunteers: A 3-Year Perspective.” *Scientific Studies of Reading,* 1(3): 277-300.

Katz, Hagai. 2014. “Poverty and Other Factors Affecting the Location of Nonprofit Human Service Organizations.” *International Journal of Social Work and Human Services Practice Horizon Research Publishing*, 2(5): 163-172

Leana, Carrie R. and Frits K. Pil. 2006. ”Social Capital and Organizational Performance: Evidence from Urban Public Schools.” *Organization Science,* 17(3): 353-366

Lee, Valerie E., and David T. Burkam. 2002. *Inequality at the starting gate: Social background differences in achievement as children begin school*. Washington, DC: Economic Policy Institute.

Mason, Jana M. 1980. “When Do Children Begin to Read: An Exploration of Four Year Old Children's Letter and Word Reading Competencies” *Reading Research Quarterly*, 15(2): 203-227.

McDouble, Lindsey M. and Marcas Lam. 2014. “Individual- and Community-Level Determinants of Public Attitudes Towards Nonprofit Organizations.” *Nonprofit and Voluntary Sector Quarterly*, 43(4): 672-692.

McKown, C. and Weinstein, R. S. 2002. “Modeling the Role of Child Ethnicity and Gender in Children's Differential Response to Teacher Expectations.” *Journal of Applied Social Psychology*, 32: 159–184.

National Center for Charitable Statistics and Independent Sector. 2002. T*he New Nonprofit Almanac and Desk Reference.* Waldorf, MD: Jossey-Bass.

National Science Board. 2014. Science and Engineering Indicators 2014. Arlington VA: National Science Foundation (NSB 14-01).

OECD. 2007. Education at a Glance 2007: OECD Indicators. http://www.oecd.org/document/30/0,3343,en 2649 39263238 39251550 1 1 1 1,00.html.

Pianta, Robert, and Daniel Walsh. 1996. *High-risk children in schools: Constructing sustaining relationships*. New York, NY: Routledge.

Pianta, Robert C., Martha J. Cox,. and Kyle L. Snow. 2007. *School Readiness and the Transition to Kindergarten in the Era of Accountability.* Baltimore, MD: Paul H. Brooks

Reich, Rob. 2005. "A Failure of Philanthropy: American charity shortchanges the poor, and public policy is partly to blame." *Stanford Social Innovation Review,* 3(4): 24-33.

Ritter, Gary W., Joshua H. Barnett, George S. Denny and Ginger R. Albin. 2009. "The Effectiveness of Volunteer Tutoring Programs for Elementary and Middle School Students: A Meta-Analysis." *Review of Educational Research,* 79(7): 3-38

Rose-Ackerman, Susan. 1996. "Altruism, Nonprofits, and Economic Theory." *Journal of Economic Literature,* 34(2): 701-728.

Salamon, Lester M., Leslie C. Hems, and Kathryn Chinnock. 2000. "The Nonprofit Sector: For What and for Whom?" *Working Papers of the Johns Hopkins Comparative Nonprofit Sector Project*, 37. Baltimore: The Johns Hopkins Center for Civil Society Studies.

Sénéchal, Monique and Laura Young. 2008. “The Effect of Family Literacy Interventions on Children's Acquisition of Reading from Kindergarten to Grade 3: A Meta-Analytic Review” *Review of Educational Research,* 78(4): 880-907

Shonkoff, Jack P. and Deborah Phillips. 2000. *From Neurons to Neighborhoods: The Science of Early Childhood Development.* Washington, DC: National Academy Press.

Snow, Catherine E., Susan M. Burns, and Peg Griffin. 1998. *Preventing Reading Difficulties in Young Children.* Washington, D.C.: National Academy Press.

U.S. Department of Education. 2002. *No Child Left Behind (NCLB) Act of 2001*, Pub. L. No. 107-110, 115, Stat. 1425 .

Varnhagen, Connie K., Frederick J. Morrison, and Robin Everall. 1994. “Age and schooling effects in story recall and story production.” *Developmental Psychology*, 30, 969-979.

# Vita

Robert (b. 1988, Philadelphia) focuses his work on the sociology of education with an interest in public-school/nonprofit partnerships, stratification, and inequality.

Permanent email: rwress@utexas.edu
This thesis was typed by Robert Wayne Ressler